

# STA257

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# permutations and combinations

At the very least we'll need to recall (or learn!) these.

Number of ways to choose  $k$  items out of  $n$  where order matters:

$${}_nP_k = \begin{cases} 0 & \text{if } k > n, \\ \frac{n!}{(n-k)!} & \text{otherwise.} \end{cases}$$

and when order doesn't matter:

$${}_nC_k = \binom{n}{k} = \frac{n!}{k!(n-k)!}$$

Two classic examples: "The Birthday Problem" and "Lotto"

**conditional probability**

# partial information

I'll roll a six-sided die.  $S = \{1, 2, 3, 4, 5, 6\}$ . Consider these events:

$$A = \{2, 5\},$$

$$B = \{2, 4, 6\},$$

$$C = \{1, 2\}.$$

$$\text{So } P(A) = \frac{2}{6} = \frac{1}{3}.$$

What if I peek and tell you "Actually,  $B$  occurred". What is the probability of  $A$  given this partial information? It is  $\frac{1}{3}$ .

I roll the die again, peek, and tell you "Actually,  $C$  occurred". Now the probability of  $A$  is  $\frac{1}{2}$ .

Intuitively we used a "sample space restriction" approach.

# elementary definition of conditional probability

Given  $B$  with  $P(B) > 0$ ,

$$P(A | B) = \frac{P(A \cap B)}{P(B)}$$

"The conditional probability of  $A$  given  $B$ "

The answers for the previous example coincide with the intuitive approach.

Theorem 7: For a fixed  $B$  with  $P(B) > 0$ , the function  $P_B(A) = P(A | B)$  is a probability measure.

Proof: exercise.

# useful expressions for calculation - I

$P(A \cap B) = P(A | B)P(B)$  often comes in handy.

Consider the testing for, and prevalence of, a viral infection such as HIV.

Denote by  $A$  the event "tests positive for HIV", and by  $B$  the event "is HIV positive."

For the ELISA screening test,  $P(A | B)$  is about 0.995. The prevalence of HIV in Canada is about  $P(B) = 0.00212$ .

# useful expressions for calculation - II

Take some event  $B$ . The sample space can be divided in two into  $B$  and  $B^C$ .

This is an example of a *partition* of  $S$ , which is generally a collection  $B_1, B_2, \dots$  of disjoint events (could be infinite) such that  $\bigcup_i B_i = S$ .

Theorem 8: If  $B_1, B_2, \dots$  is a partition of  $S$  with all  $P(B_i) > 0$ , then

$$P(A) = \sum_i P(A \mid B_i)P(B_i)$$

Proof: ...

Continuing with the HIV example, suppose we also know  $P(A \mid B^c) = 0.005$  ("false positive").

We can now calculate  $P(A)$ .

# useful expressions for calculation - III

Much to my amusement, Theorem 8 gets a grandiose title: ***"THE! LAW! OF! TOTAL! PROBABILITY!!!"***

Now, in the HIV example, we also might be interested in  $P(B|A)$ , the chance of an HIV+ person testing positive.

A little algebra:

$$P(B | A) = \frac{P(B \cap A)}{P(A)} = \frac{P(A | B)P(B)}{P(A | B)P(B) + P(A | B^c)P(B^c)}$$

In our example this is  $\frac{0.0021094}{0.0070988} = 0.2971$ .



# Bayes' rule

Theorem 9: If  $B_1, B_2, \dots$  is a partition of  $S$  with all  $P(B_i) > 0$ , then

$$P(B_i | A) = \frac{P(A | B_i)P(B_i)}{P(A)} = \frac{P(A | B_i)P(B_i)}{\sum_i P(A | B_i)P(B_i)}$$

Proof:

**independence**

# motivation - revisit the die toss example

I'll roll a six-sided die.  $S = \{1, 2, 3, 4, 5, 6\}$ . Consider these events:

$$A = \{2, 5\},$$

$$B = \{2, 4, 6\}$$

$$\text{So } P(A) = \frac{2}{6} = \frac{1}{3}.$$

What if I peek and tell you "Actually,  $B$  occurred". What is the probability of  $A$  given this partial information? It is  $\frac{1}{3}$ .

**The probability of  $A$  didn't change after the new information:**

$$P(A | B) = \frac{P(A \cap B)}{P(B)} = P(A)$$

# *definition(s)* of independence

$A$  and  $B$  are (pairwise) *independent* (notation  $A \perp B$ ) if:

$$P(A \cap B) = P(A)P(B)$$

No requirement for  $P(A)$  or  $P(B)$  to be positive. In fact ... see the suggested problems for Chapter 1.

$A_1, A_2, A_3, \dots$  (possibly infinite) are (mutually) *independent* if for any finite subcollection of indices  $I = \{i_1, \dots, i_n\}$ :

$$P\left(\bigcap_{i \in I} A_i\right) = \prod_{i \in I} P(A_i)$$

# independence of two classes of events

Note that if  $A \perp B$ , then also  $A \perp B^c$  and so on. Consider:

$$\mathcal{A} = \{\emptyset, A, A^c, S\}$$

$$\mathcal{B} = \{\emptyset, B, B^c, S\}$$

Classes of events  $\mathcal{A}$  and  $\mathcal{B}$  are *independent* all pairs of events with one chosen from each class are independent.

This suggests a concept of "independent experiments", which will be revisited.

# the "any" and "all" style of examples

(Note: in probability modeling, independence is usually *assumed*.)

A subway train is removed from service if *any* of its doors are stuck open. There is a probability  $p$  of a door getting stuck open on one day of operations. A train has  $n$  doors.

What is the chance a train is removed from service due to stuck doors on one day of operations?

real valued functions with  
arguments that live inside sample  
spaces

# the main focus of this course

We'll use "probability measure" throughout the course, but our main focus will be a different and equally strange object entirely.

Recall that sample space is often arbitrary and difficult or impossible to describe.

Usually we're ultimately interested in a number that is associated with the random outcome, rather than the outcome itself.

Consider a coin tossing game with  $S = \{H, T\}$ , which might be repeated, from which a multitude of examples can be invented.



# *random variable*

A *random variable* is a real valued function of a sample space.

Naming convention: Roman letters near the end of the alphabet  $X, Y, X_1, X_2, \dots$

Another strange convention - almost always omit the function's "argument".

We will never draw a picture of a random variable, or compute a derivative or an integral of one.

We will instead focus on *the* defining property of a random variable: its *distribution*.

Perversely, we will lack the math to actually define *distribution* rigorously. Informally, the *distribution* of a random variable  $X$  is the rule that assigns probabilities to values of  $X$ .